Carry Trades and Endogenous Regime Switches in Exchange Rate Volatility*

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Abstract

This paper investigates the profitability of carry trades by taking into account the endogeneity of regime switching between low and high states of exchange rate volatility. The analysis uses an endogenous regime switching model with an autoregressive latent factor, in which the future transition between states depends on the current state as well as the realization of the underlying time series. The results show that carry trades are profitable in a regime with low exchange rate volatility, signifying the failure of uncovered interest rate parity (UIP). However, carry trades yield losses in a regime with high exchange rate volatility, which implies a reversion to UIP. The endogenous latent factor obtained from the model represents historical economic downturns associated with carry trade losses well. It also appears to exhibit a similar pattern to those of two measures of uncertainty, macroeconomic uncertainty and economic policy uncertainty.

JEL Classification: C32; F31; G15

Keywords: Endogenous regime switching model; Carry trades; Exchange rate volatility; Latent factor; Uncovered interest rate parity

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1 Introduction

An important issue in international finance is the apparent failure of the theory of uncovered interest rate parity (UIP). The theory of UIP predicts that a high interest rate currency will depreciate relative to a low interest rate currency. That is, the theory requires that the interest rate differential between two countries be offset completely by an expected depreciation of the high interest rate currency or, equivalently, by an expected appreciation of the low interest rate currency. However, empirical studies show that the high interest rate currency tends to appreciate rather than depreciate, which is referred to as a violation of UIP. A carry trade, which exploits this phenomenon, is a currency investment strategy where an investor borrows in a low interest rate currency, known as a funding currency, and then invests in a high interest rate currency or target currency. Clearly, carry traders are speculating on the violation of UIP, or the existence of the forward premium anomaly, by engaging in short-run positions in order to make a profit.[1]

Many studies have investigated the profitability of carry trades. Among others, Brunnermeier et al. (2008) show that carry trade profitability is related to the interest rate differential between the target currency and the funding currency. They provide evidence that carry traders are exposed to a high "crash risk".[2] Menkhoff et al. (2012) investigate the relation between global foreign exchange volatility and the cross section of carry trade excess returns. They find that high interest rate currencies are negatively related to innovations in global foreign exchange volatility, leading to low returns in times of unexpected high volatility. Baillie and Chang (2011) show that a carry trade is more likely to be unprofitable in a regime where exchange rate volatility is unusually high. They analyze carry trades based on the limits to speculation hypothesis as explained by Lyons (2001).[3] Baillie and Cho (2014a) relate relative interest rate opportunities to the returns (i.e., the interest rate differential between the target currency and the funding currency) on carry trades, representing the periods when the carry trade was profitable and when it was not.[4]

[1] Carry trades are also known to involve excessive risk because they are exposed to any sudden and unexpected changes in exchange rates.

[2] When there is a large and positive interest rate differential between the target currency and the funding currency, carry trade returns are negatively skewed.

[3] The limits to speculation hypothesis of Lyons (2001) implies that the presence of higher than usual profit opportunities from carry trades attracts speculative capital, inducing investors to trade these profit opportunities away. In contrast, when the profits from carry trades are low or negative, the forward bias remains unexploited, thus, persists.

[4] They provide evidence that the desirability of carry trades has declined for many currencies and that such trades have actually become unprofitable since the financial crisis of 2008.

It has become fashionable to assume the forward premium anomaly as a stylized fact in international finance. It is also known that carry trades appear to be profitable in periods when the forward premium anomaly or the violation of UIP persists. However, Bansal (1997) and Baillie and Bollerslev (2000) show that the estimated slope parameter in the standard forward premium regression is time-varying. More recently, Baillie and Cho (2014b) provide evidence of substantial time variation in both the existence and the magnitude of the forward premium anomaly for many of the major currencies against the US dollar over the last 30 years. Thus, the forward premium anomaly is perceived to be apparently a time-varying phenomenon.

In this paper, we investigate the relation between exchange rate volatility and the profitability of carry trades using a model recently proposed by Chang et al. (2017)—an endogenous regime switching model with an autoregressive latent factor. This model has the advantage of identifying whether the currency market is in a regime with low or high exchange rate volatility. In the model, the endogeneity of regime switching is driven by the autoregressive latent factor, which is correlated with the realization of innovation. That is, the future transition between states depends on the current state as well as the realization of the underlying time series. This is in sharp contrast to the conventional Markov switching model, in which the future transition is completely determined by the current state only and do not depend on the realization of the underlying time series (see Driffill and Sola, 1998). Furthermore, Chang et al. (2017) note that if the autoregressive latent factor becomes exogenous, the endogenous regime switching model reduces to the conventional Markov switching model.[5]

As mentioned in Ichiue and Koyama (2011), analyzing exchange rates using regime switching models is not new. Examples of studies that have used this approach include those of Hamilton (1989), Engel and Hamilton (1990), Bekaert and Hodrick (1993), Engel (1994), Bollen et al. (2000), and Dewachter (2001). Of these, the current study is most closely related to that of Ichiue and Koyama (2011) that examine how exchange rate volatility is related to the failure of UIP using a conventional Markov switching model.[6] They show that a low volatility environment is influenced by short term carry trade activities, and that their rapid unwinding influences exchange

[5]Thus, the endogenous regime switching model can be regarded as a generalization of the conventional Markov switching model by relaxing some of its important restrictions.

[6]They employ a four-regime conventional Markov switching model, which makes it less restrictive than other models.

rates substantially. Our approach differs from theirs as our model takes into account the "endogeneity" of regime switching which can be regarded as a novel aspect of this study.

It is worth noting that we explore how exchange rate volatility, rather than stock market volatility, is related to the profitability of carry trades, or the violation of UIP.[7] For five major currencies, we show that while a carry trade is profitable in a regime with low exchange rate volatility, it becomes unprofitable in a regime with high exchange rate volatility. This implies that in a low volatility environment, the forward premium anomaly or the violation of UIP tends to persist, whereas, in a high volatility environment, a reversal of the anomaly, or a reversion to UIP occurs. This is also in line with the findings of Ranaldo and Söderlind (2010) and Ichiue and Koyama (2011): a depreciation (an appreciation) of a currency with a low interest rate is associated with a low (high) volatility environment. We also find evidence of endogeneity in regime switching in exchange rate volatility. It appears to distinguish between a target currency with a high interest rate and a safe haven currency that provides hedging in turbulent periods. The latent factor obtained from the model appears to represent historical economic downturns, associated with carry trade losses well. Interestingly, the extracted latent factor exhibits a similar pattern to that of the macroeconomic uncertainty index of Ozturk and Sheng (2017) and the measure of economic policy uncertainty (EPU) of Baker et al. (2016). Furthermore, the estimated time varying transition probability is found to change dramatically during turbulent periods when exchange rate volatility is high.

The remainder of this paper is organized as follows. In Section 2, we explain carry trades and the forward premium anomaly. In Section 3, we introduce the model with endogenous regime switching and describe the estimation procedure. In Section 4, we describe the data and interpret the estimation results. In Section 5, we conclude the paper.

2 Carry trades and the forward premium anomaly

In this section, we explain the relation between a carry trade and the forward premium anomaly. As Baillie and Cho (2014a) note, the profitability of a carry trade is related to the extent of the

[7] For instance, Brunnermeier et al. (2008) show that currencies with low interest rates are more likely to appreciate sharply when VIX, a stock market volatility measure, is higher. That is, when stock market volatility increases, a rapid reversal to UIP tends to occur.

failure of UIP, or the forward premium anomaly. The ex-post returns to the carry trade at time t are defined as

$$r_t = \left(i^*_{t-1} - i_{t-1}\right) - \Delta s_t \tag{1}$$

where s_t is the logarithm of the spot exchange rate quoted as the foreign price of a domestic currency, and i_t and i^*_t are the one-period, risk-free domestic and foreign interest rates, respectively. Essentially, carry traders attempt to exploit the interest rate differential between two countries. When they close a carry trade position, the profitability of the carry trade depends on whether the high (low) interest rate currency depreciates (appreciates). If UIP holds, then the rate of return on a currency should equal the lagged interest rate differential

$$\Delta s_t = \left(i^*_{t-1} - i_{t-1}\right) = \left(f_{t-1} - s_{t-1}\right) \tag{2}$$

where f_t is the logarithm of the forward exchange rate for a one-period-ahead transaction, quoted as the foreign price of the domestic currency. The last equality is implied by covered interest rate parity (CIP). Following Fama (1984), the test for the theory of UIP has been to estimate the econometric model

$$\Delta s_t = \beta_0 + \beta_1 \left(f_{t-1} - s_{t-1}\right) + \varepsilon_t \tag{3}$$

If UIP holds, the null hypothesis to be tested is that $\beta_0 = 0$, $\beta_1 = 1$, and that the error term, ε_t, is serially uncorrelated.[8] Fama (1984) shows the existence of the forward premium anomaly, where the estimate of the slope coefficient is negative and significantly different from the value of unity as implied by the theory of UIP. In their study, Froot and Thaler (1990) find that the average value of the estimated slope coefficients across 75 published articles is –0.88.

Previous studies have attempted to account for the forward premium anomaly based mostly on (i) the presence of a time varying risk premium, (ii) irrational agents in segmented markets, (iii) peso problems, and (iv) econometric issues arising in the test of UIP.[9] Baillie and Bollerslev (2000) and Maynard and Phillips (2001) consider econometric issues arising from the statistical

[8] As noted by Fama (1984), this is equivalent to testing whether $\omega = 0$ and $\gamma = 0$ in the following regression: $r_t = \omega + \gamma \left(f_{t-1} - s_{t-1}\right) + \xi_t$, where ξ_t is a disturbance. If γ is negative and significantly different from zero, it leads to apparent carry trade return predictability and the failure of UIP.

[9] As explained by Bansal (1997), the sign of the forward premium, $(f_t - s_t)$, is an important indicator on the magnitude of the anomaly, implying the asymmetry of the anomaly.

properties: regressing the markedly volatile and uncorrelated spot returns on the very persistent, highly autocorrelated forward premium. Hodrick (1987) and Engel (1996) provide extensive surveys of the forward premium anomaly, including possible resolutions. In addition, Bacchetta (2012) provides some explanations for the forward premium anomaly based on the risk premium, limited market participation, and deviations from rational expectations. In many related studies, the forward premium anomaly is also known to be robust to the choice of the numeraire currency, as well as across different periods.

Table 1 reports the estimation results from the linear regression model in (3) with the USD as the numeraire currency. The slope coefficients of interest are all negative except for the EUR and JPY, which exhibit positive slope coefficients of 0.684 and 0.067, respectively. In addition, the null hypothesis of the slope coefficient being unity is rejected for the AUD at the 5% significance level and for the GBP at the 1% significance level. Interestingly, the AUD and the GBP, which are classified as target currencies associated with high interest rates in our sample, clearly exhibit evidence of the forward premium anomaly.

In what follows, we investigate the profitability of carry trades using a regime switching model where regime switching is determined endogenously. The model is able to identify whether a regime is characterized by high or low exchange rate volatility. We then analyze the relation between exchange rate volatility and the profitability of carry trades over the past 30 years.

3 The model

Previous studies have typically investigated the dynamics between spot returns and the lagged forward premium using Equation (3). We allow for regime switching in (3), and let the parameters take different values for each state of the regime. We consider two states: a high volatility state and a low volatility state. The unique feature of our approach is that we adopt the endogenous regime switching method recently introduced by Chang et al. (2017), rather than the conventional Markov switching approach. Therefore, the current realization of the underlying time series (i.e., the rate of return on a currency) affects the state of the regime in the following period, which allows for more realistic regime switching dynamics in the model.

In the conventional Markov switching model, the Markov chain selecting the state of the regime is completely independent of all other parts of the model. In other words, the future transition between states in the Markov switching model is determined entirely by the current state, and do not depend on the realization of the underlying time series, which is unrealistic in many cases. On the other hand, in the endogenous regime switching model of Chang et al. (2017), the future transition between the states depends on the realization of the underlying time series as well as the current state.[10] Moreover, as shown by Chang et al. (2017), the endogenous regime switching model can encompass the conventional Markov switching model, because it becomes observationally equivalent to the conventional Markov switching model when the autoregressive latent factor is exogenous. See Section 2.2 in Chang et al. (2017) for more details on the relationship between the endogenous regime switching model and the conventional Markov switching model.

The new model proposed by Chang et al. (2017) utilizes an autoregressive latent factor, which determines the state of the regime. It is possible to extract the latent factor and to use it to explicitly characterize each state of the regime. When we compare the extracted latent factor with economic situations, it provides interesting economic interpretations on the dynamics of exchange rates. The transition probability also depends on the realization of the underlying time series and, consequently, is time-varying in the endogenous regime switching model. This is more realistic than the conventional Markov switching model, in which the transition probability between states is constant. The estimated transition probability also provides useful information on the dynamics of exchange rates.

Specifically, we consider

$$\Delta s_t = c + \mu(\mathbb{S}_t)(f_{t-1} - s_{t-1}) + \sigma(\mathbb{S}_t)u_t. \tag{4}$$

The state process $(\mathbb{S}_t)$ represents the low or high state, depending on whether it takes the value zero or one;

$$\mathbb{S}_t = 1\{\omega_t \geq \tau\}, \tag{5}$$

[10] Kim et al. (2008) also propose a regime switching model allowing for endogeneity. Their model postulates the presence of a contemporaneous correlation between the state variable and the innovation of the underlying time series, whereas the innovation in Chang et al. (2017) is assumed to be correlated with the state variable in the subsequent period. See Chang et al. (2017) for more details.

where $1\{\cdot\}$ is the indicator function. Given the realized value of the latent factor ω_t and the threshold level τ, we interpret the two events $\{\omega_t < \tau\}$ and $\{\omega_t \geq \tau\}$ as two regimes that are switched. The state-dependent parameters μ and σ in (4) are switched between the two regimes such that $\mu(\mathbb{S}_t) = \lambda_l(1-\mathbb{S}_t) + \lambda_u \mathbb{S}_t$ and $\sigma(\mathbb{S}_t) = \sigma_l(1-\mathbb{S}_t) + \sigma_u \mathbb{S}_t$.[11]

The latent factor (ω_t) is assumed to be an autoregressive process of order 1 (AR(1))

$$\omega_t = \alpha \omega_{t-1} + v_t$$

for $\alpha \in (-1, 1]$, and correlated with the previous innovation in the model. Specifically, (u_t) and (v_t) are jointly independent and identically distributed (iid) as

$$\begin{pmatrix} u_t \\ v_{t+1} \end{pmatrix} =_d N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right). \tag{6}$$

If u_t and v_{t+1} are correlated (that is, $\rho \neq 0$), the latent factor ω_{t+1} is correlated with the observed spot exchange rate return Δs_t. This means that the future transition between states is endogenously affected by the current spot exchange rate return Δs_t because the latent factor ω_{t+1} determines the future state $\mathbb{S}_{t+1}$ in (5). However, if u_t and v_{t+1} are uncorrelated (i.e., $\rho = 0$), such an endogenous channel does not work. Hence, if $\rho = 0$, it becomes an exogenous regime switching model because the future transition between states at time t does not depend on the observed Δs_t. Chang et al. (2017) show that if $\rho = 0$ together with $|\alpha| < 1$, the endogenous regime switching model reduces to the conventional Markov switching model.[12] This is why they argue that the endogenous regime switching model can be regarded as an extended form of the Markov switching model.

To estimate the model, we adopt the maximum likelihood estimation method and use the modified Markov switching filter as explained in Chang et al. (2017). The conventional Markov switching filter is not applicable because the state process $(\mathbb{S}_t)$ in (5) is not a Markov chain when $\rho \neq 0$. See Section 3 in Chang et al. (2017) for more details.

[11] We also consider a model where we let the intercept parameter c be state-dependent as are μ and σ. However, the results remain qualitatively similar to those obtained from the model with a fixed c.

[12] See Section 2.2 in Chang et al. (2017) for further details.

4 Empirical analysis

4.1 Data

This paper uses data on five major currencies from advanced economies covering the last three decades. The five currencies are the Australian dollar (AUD), the Swiss franc (CHF), the euro (EUR), the British pound (GBP), and the Japanese yen (JPY).[13] The data are spot and one-month forward exchange rates, vis-à-vis the US dollar (USD), for the period January 1985 through December 2016. They are collected from *Datastream* and comprise a total of 384 observations for each currency pair. The following two indices of country-specific uncertainty are also obtained to determine whether the endogenous regime switching model can explain the current state of uncertainty or risk: i) the macroeconomic uncertainty index of Ozturk and Sheng (2017) and ii) the index of economic policy uncertainty (EPU) of Baker et al. (2016).

4.2 Parameter estimates

We estimate the endogenous regime switching model in (4) using spot and forward exchange rates. The estimation results are reported in Table 2. Here, μ_l and μ_u denote the estimated coefficients of the forward premium in a low volatility and a high volatility regime, respectively. In a low volatility regime, the estimated coefficients are all negative, ranging from –3.233 to –1.507. The null hypothesis of $\mu_l = 1$ is strongly rejected at the 1% significance level for four of the currencies, with the exception of the EUR, where the null hypothesis is rejected at the 5% level. The statistically significant negative coefficient implies that in normal times, the forward premium anomaly or the failure of UIP persists, in which case, carry trades appear to be profitable, on average. As explained above, a carry trade exploits the forward premium anomaly or the failure of UIP.

In contrast, in a high volatility regime, the estimated coefficients are positive, ranging from 1.021 for the AUD to 7.043 for the CHF. In this case, the GBP is an exception, exhibiting a negative value of –1.036. The null hypothesis of $\mu_u = 1$ cannot be rejected for the AUD, EUR, or JPY but can be rejected for the CHF at the 5% level. A positive value exceeding unity implies a

[13]For the period prior to the introduction of the euro in January 1999, we use the Deutsche mark/US dollar exchange rate adjusted by the official conversion rate between the euro and the Deutsche mark.

reversal of the forward premium anomaly and the apparent collapse of gains from carry trades. This is consistent with the finding of Baillie and Chang (2011), which show that the theory of UIP holds in an upper regime where exchange rate volatility was high.[14] In addition, Baillie and Cho (2014a) show that the profitability of carry trades decreased for many currencies in turbulent periods, such as the 2008 global financial crisis when exchange rate volatility is high. As explained by Brunnermeier et al. (2008), higher market volatility may correspond to periods of decreased investor risk tolerance and tighter liquidity and funding constraints. This is also associated with the unwinding of carry trades which leads to losses: when investors' risk tolerance decreases and they approach their liquidity and funding constraints, carry trades are unwound, which leads to bad payoffs of carry trades.[15]

The estimates for the endogeneity parameter (ρ) range between 0.249 and 0.807, except for the JPY, with an estimate of –0.837.[16] The null hypothesis of no endogeneity can be rejected at the 10%, 10%, and 5% significance levels for the AUD, GBP, and JPY, respectively. This provides evidence of endogeneity in regime switching in exchange rate volatility. Interestingly, the AUD and GBP, which are associated with high interest rates, are considered to be target currencies among carry traders. The positive value of the correlation implies that while a positive shock to the spot returns (Δs_t) at time t in (4) increases the probability of having a high volatility regime at time $t+1$, a negative shock to the spot returns increases the probability of having a low volatility regime at time $t+1$. This means that during turbulent periods, investors are likely to unwind carry trade positions due to tighter funding and liquidity constraints, leading to depreciations of the target currencies. This increases the volatility of the target currencies. However, during normal times, investors tend to engage in carry trades, which are, in turn, associated with appreciations of the target currencies. This results in reduced future volatility. Similarly, given the strong negative value of the correlation for the JPY, a positive shock to the spot returns at time t in

[14]Baillie and Chang (2011) show that a reversion to UIP is more likely to occur in periods of high volatility, implying that carry trades tend to yield losses when markets become more turbulent.

[15]As also pointed out by Brunnermeier and Pedersen (2009), during turbulent periods, investors' risk aversion increases, in turn, sudden and massive unwinding of carry trade positions leads to rapid reversals of exchange rates. Thus, low interest rate currencies start to appreciate to a greater extent than that implied by the theory of UIP.

[16]If the endogeneity parameter (ρ) is not zero, the shock to the current spot exchange rate return Δs_t affects the future latent factor ω_{t+1}, which determines the future state $\mathbb{S}_{t+1}$ in (5). As shown in (6), such an endogenous feedback effect is stronger for a higher absolute value of parameter (ρ). In other words, higher absolute values of the the endogeneity parameter (ρ) imply that the shock to the current spot exchange rate return at time t has a stronger influence on the future transition between states.

(4) increases the probability of having a low volatility regime at time $t+1$. In contrast, a negative shock to the spot returns increases the probability of having a high volatility regime at time $t+1$. In contrast to what happens during normal periods, in turbulent periods, investors may turn to safe haven currencies such as the CHF or JPY, that could provide hedging benefits, leading to appreciations of these currencies and greater future volatility, as documented by Brunnermeier et al. (2008) and Ranaldo and Söderlind (2010).

The autocorrelation coefficient (α) is estimated to be between 0.901 and 0.999, implying high persistence of the latent factor (ω_t). If the latent factor is more persistent, there will be fewer regime switches. The threshold level (τ) is estimated in the range of 1.869 and 9.259. The extracted latent factor and the estimate of the threshold level determine regimes as shown in (5). The extracted latent factor represents unobserved economic fundamental and the threshold level is a certain level of the latent factor by which the regime (or the status of economic fundamental) switches. One of the advantages of adopting the endogenous regime switching model is that we can explicitly identify each regime by using the extracted latent factor and the estimated threshold level. We show and explain low volatility and high volatility regimes identified for each currency in the next subsection. The estimated parameters for σ_ℓ and σ_u indicate that the level of volatility in a high volatility regime appears to be approximately twice as large as that in a low volatility regime.

Table 3 reports the average carry trade excess return (%) with transaction costs (that is, using the bid and ask rates) for low and high volatility regimes, respectively.[17] For the target currency associated with a high interest rate, such as the AUD and GBP, while it is positive in a low volatility regime (0.251% and 0.139%, respectively), it is negative in a high volatility regime (–0.100% and –0.017%, respectively). This implies that carry traders invests in target currencies in normal periods, which leads to appreciations of these currencies. Contrary to this, for the safe haven currency, such as the CHF, EUR, and JPY, the average carry trade return appears to be much greater in a high volatility regime than in a low volatility regime. As explained above, this implies that in turbulent periods, investors may turn to safe haven currencies such as the CHF, EUR, and JPY, that could provide hedging benefits, leading to appreciations of these currencies and greater

[17] We first identify low and high volatility regimes over the sample period through the estimation of the endogenous regime switching model and then obtain the average value of the carry trade excess returns for the periods that correspond to low and high volatility regimes, accordingly.

future volatility. This pattern can be observed apparently for the CHF, EUR, and JPY: while the average carry trade return is negative in a low volatility regime (–0.019, –0.048, and –0.153, respectively), it becomes positive in a high volatility regime (0.076, 0.109, and 0.084, respectively). Taken together, it clearly separates cases of a target currency with a high interest rate and of a safe haven currency providing hedging benefits in turbulent periods. This is also in line with the findings of Ranaldo and Söderlind (2010).[18]

4.3 Latent factor and transition probabilities

Figure 1 depicts the carry trade return (%) and the extracted latent factor from the model for the five currencies. Shaded areas indicate periods corresponding to a high volatility regime. The extracted latent factor appears to represent historical economic downturns associated with carry trade losses quite well.[19] Obviously, the recent global financial crisis belongs to a high volatility regime for all five currencies. For the CHF, EUR, and GBP in the euro area, the European exchange rate mechanism (ERM) crisis of 1992–1993 is also associated with a high volatility regime. For the JPY, the Asian financial crisis of 1997–1998 corresponds to a high volatility regime.

Figure 2 shows the transition probabilities estimated using the conventional Markov switching model and the endogenous regime switching model. As pointed out by Chang et al. (2017), whereas the transition probability estimated by the conventional Markov switching model is constant over the sample period, the corresponding transition probabilities estimated by the endogenous regime switching model vary over time. For the endogenous regime switching model, the transition probabilities depend on the lagged value of the rate of return on the currency as well as the realized value of the previous state $\mathbb{S}_{t-1}$. The left hand graph shows the transition probability from the low volatility regime at $t-1$ to the high volatility regime at t, estimated using the conventional Markov switching model and the endogenous regime switching model. This constant "low to high" transition probability ($P\left(\mathbb{S}_t = 1 \,|\mathbb{S}_{t-1} = 0\right)$), denoted by the dashed red line, is estimated to be 6.71%, 6.54%, 1.05%, 1.31%, and 11.11% over the sample period for the AUD, CHF, EUR, GBP, and JPY, respectively, by the conventional Markov switching model. How-

[18]Our approach appears to be somewhat different from that of Ranaldo and Söderlind (2010) as we deal with volatility for the individual currency and they use overall currency market volatility. However, we provide essentially similar results to those of Ranaldo and Söderlind (2010).

[19]It is worth noting that the endogenous latent factor (ω_t) may be regarded as an economic fundamental determining the regimes of an economy, as explained in Chang et al. (2017).

ever, the corresponding transition probabilities estimated by the endogenous regime switching model vary over time. The solid blue line signifies the time varying transition probability of $P(\mathbb{S}_t = 1 | \mathbb{S}_{t-1} = 0, \Delta s_{t-1})$. For the AUD, the probability peaks at 74.22% during the global financial crisis period. For the CHF, the two highest probabilities are estimated to be 20.52% and 20.04%, during the ERM crisis period and the global financial crisis period, respectively. For the EUR, the highest transition probability is 4.85%, during the ERM crisis period, followed by 3.98% during the global financial crisis period. For the GBP, the probability peaks at 15.86% during the ERM crisis period and is 9.69% during the global financial crisis period. Lastly, for the JPY, the highest transition probability is estimated to be 60.20% during the Asian financial crisis period, and 18.06% during the global financial crisis period. This suggests that the transition probability estimated by the endogenous regime switching model reflects changes in exchange rates well as opposed to the constant transition probability generated by the conventional Markov switching model.

Similarly, the right hand graph demonstrates the transition probabilities from the high volatility regime at $t-1$ to the high volatility regime at t estimated by the conventional Markov switching model and by the endogenous regime switching model. This constant transition probability, remaining in a high volatility regime ($P(\mathbb{S}_t = 1 | \mathbb{S}_{t-1} = 1)$), denoted by the dashed red line, is estimated to be 77.39%, 82.69%, 98.61%, 98.37%, and 81.31% over the sample period for the AUD, CHF, EUR, GBP, and JPY, respectively, by the conventional Markov switching model. In contrast, the solid blue line indicates the time varying transition probability of $P(\mathbb{S}_t = 1 | \mathbb{S}_{t-1} = 1, \Delta s_{t-1})$. For all the currencies, the transition probabilities estimated by the endogenous regime switching model differ markedly from the one obtained from the conventional Markov switching model. When the observed rate of return on a currency is high, the transition probability from a high regime to a high regime is high. However, these transition probabilities tend to increase during the aforementioned turbulent periods.

4.4 Comparison of the latent factor with uncertainty measures

Chang et al. (2017) provide an empirical illustration of regime switching in US stock return volatility. Because the salient feature of the endogenous regime switching model is the extracted latent factor, which varies over time, they compare the latent factor and the VIX. Specifically, to determine how well the endogenous regime switching model reflects the current market volatility, they compare the sample paths of the extracted latent factor with that of the VIX for the subsample period 1990 to 2012, where VIX data are available.[20] They show that the extracted latent factor from the model can be considered as an alternative measure, because it plays a similar role to that of the VIX. Similarly, we explore whether the extracted latent factor from our model could be considered as an alternative measure of economic uncertainty related to the exchange rate. The extracted latent factor obtained from our model represents underlying economic fundamentals that determine the states of exchange rate volatility. Thus, it can be related to the current state of economic uncertainty or risk for each country.

We examine whether the extracted latent factor could be considered as an alternative measure of economic uncertainty by comparing it with the existing measures of economic uncertainty. We consider i) the macroeconomic uncertainty index of Ozturk and Sheng (2017), and ii) the index of economic policy uncertainty (EPU) of Baker et al. (2016). These measures appear to be the most appropriate for our purpose because they are country-specific among various uncertainty indices. Using individual survey data from the Consensus Forecasts, Ozturk and Sheng (2017) propose a monthly index of country-specific macroeconomic uncertainty, and show that it is able to capture the perceived uncertainty of market participants. The second index is a measure of economic policy uncertainty based on the frequency of references to policy-related uncertainty in the newspapers as developed by Baker et al. (2016). They provide evidence that elevated policy uncertainty in the United States and Europe in recent years may have harmed macroeconomic performance. Because exchange rate volatility tends to increase in turbulent periods of high uncertainty or risk, which is closely associated with carry trade losses, we compare the sample paths of the extracted latent factor with those of the two measures of uncertainty over the sample period. However, these measures are not fully available in our sample period. The data availability for the two uncertainty measures is provided in Table 4. For the macroeconomic uncertainty index, the starting date differs across countries, but the end date is the same (July 2014). For the EPU measure, the available data periods are given accordingly. However, for

[20]The VIX is a well known measure of the stock market's expectation of volatility implied by S&P 500 index options, which is available from the Chicago Board Options Exchange (CBOE).

Switzerland, no EPU measure is available.

Figures 3 and 4 present the sample paths of the extracted latent factor and of the macroeconomic uncertainty index and the EPU measure, respectively. In both figures, the extracted latent factor appears to represent periods associated with a high level of uncertainty. For instance, in Figure 3 (d), for the GBP, the macroeconomic uncertainty index remained at a relatively low level during the period 1996–2006 and 2012, and remained high before 1995 and during the period 2007–2011. The extracted latent factor obtained from the endogenous regime switching model exhibits a similar pattern, moving closely with the measure, especially in the high volatility periods. Similarly, in Figure 4, the extracted latent factor appears to move together with the EPU measure, albeit with some deviations. For example, in Figure 4 (e), for the JPY, the EPU measure stayed relatively high during the well known turbulent periods of the Asian financial crisis of 1997–1998 and the global financial crisis of 2007–2008, with the extracted latent factor also peaking in those periods. Overall, the extracted latent factor exhibits a similar pattern to those of the two uncertainty measures, which implies that it can be an alternative measure of economic uncertainty.

5 Conclusion

This paper has investigated the desirability of carry trades by taking into account the endogeneity of regime switching between high volatility and low volatility regimes. We have employed the endogenous regime switching model recently proposed by Chang et al. (2017) with an autoregressive latent factor, which is able to determine regimes where exchange rate volatility is low or high. Notably, the proposed model allows for endogeneity in regime switching, so that a shock to the rate of return on a currency affects the change in regime. In addition, the future transition between states depends on the current state as well as the realization of the underlying time series, which is the rate of return on a currency. As emphasized by Chang et al. (2017), unless there is endogeneity in regime switching, the endogenous regime switching model becomes observationally equivalent to the conventional Markov switching model.

We show that whereas carry trades are profitable in a regime with low exchange rate volatility, signifying the failure of UIP, they yield losses in a regime with high exchange rate volatility, which implies a reversion to UIP. We also find evidence of endogeneity in regime switching in exchange rate volatility. It appears to separate cases of a target currency with a high interest rate and of a safe haven currency, which provides hedging benefits in turbulent periods. The endogenous latent factor obtained from the proposed model appears to represent historical economic downturns, such as the ERM crisis, the Asian financial crisis, and the global financial crisis, associated with carry trade losses quite well. Furthermore, it appears to exhibit a similar pattern to those of two measures of uncertainty, macroeconomic uncertainty and economic policy uncertainty. Lastly, the estimated time varying transition probability is found to change drastically during turbulent periods, when exchange rate volatility is high.

While the analysis by Ranaldo and Söderlind (2010) show distinct features of safe haven currencies using high frequency data (from a few hours to several days), they mention that statistical significance becomes weaker when lower frequency data (weekly) are considered. It should be noted that using much lower frequency data (monthly), we provide evidence of distinct features between safe haven currencies and target currencies. While we estimate the univariate model for each currency in this current study, we expect that it would be possible to obtain stronger evidence of distinct features between safe haven currencies and target currencies if one adopts a panel model approach with restrictions controlling for idiosyncratic characteristics. We leave this for future work.

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TABLE 1. ESTIMATION RESULTS OF THE LINEAR REGRESSION MODEL

$$\Delta s_t = \beta_0 + \beta_1 (f_{t-1} - s_{t-1}) + \varepsilon_t$$

	AUD	CHF	EUR	GBP	JPY
β_0	0.002	–0.003	–0.001	0.002	–0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
β_1	–0.714	–0.066	0.684	–1.276	0.067
	(0.745)	(0.824)	(0.790)	(0.793)	(0.655)
$t_{\beta_1=1}$	–2.301	–1.294	–0.399	–2.870	–1.424

Notes. The estimation results of the linear regression model are reported. Standard errors are reported below their corresponding estimates in parentheses. $t_{\beta_1=1}$ denotes the t-statistic for testing H_0: $\beta_1 = 1$.

TABLE 2. ESTIMATION RESULTS OF THE ENDOGENOUS REGIME SWITCHING MODEL

$$\Delta s_t = c + \mu(\mathbb{S}_t)(f_{t-1} - s_{t-1}) + \sigma(\mathbb{S}_t) u_t,$$

where $\mathbb{S}_t = 1\{\omega_t \geq \tau\}$, $\omega_t = \alpha\omega_{t-1} + \nu_t$, $\alpha \in (-1, 1]$,

$\mu(\mathbb{S}_t) = \mu_l(1 - \mathbb{S}_t) + \mu_u \mathbb{S}_t$ and $\sigma(\mathbb{S}_t) = \sigma_l(1 - \mathbb{S}_t) + \sigma_u \mathbb{S}_t$,

$\binom{u_t}{\nu_{t+1}} =_d N\left[\binom{0}{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$.

	AUD	CHF	EUR	GBP	JPY
c	0.002	–0.005	–0.002	0.001	–0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
μ_ℓ	–1.507	–3.233	–1.948	–2.538	–1.993
	(0.677)	(0.993)	(1.363)	(1.271)	(0.891)
μ_u	1.021	7.043	1.981	–1.036	1.519
	(1.863)	(2.940)	(1.177)	(1.059)	(1.269)
α	0.901	0.933	0.999	0.999	0.978
	(0.066)	(0.077)	(0.001)	(0.002)	(0.030)
τ	1.870	1.869	9.259	8.664	2.442
	(0.865)	(1.415)	(17.082)	(10.957)	(2.188)
ρ	0.538	0.249	0.457	0.807	–0.837
	(0.285)	(0.274)	(0.503)	(0.458)	(0.374)
σ_ℓ	0.025	0.027	0.025	0.021	0.026
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
σ_u	0.054	0.042	0.038	0.040	0.043
	(0.007)	(0.004)	(0.002)	(0.003)	(0.004)
$t_{\mu_\ell=1}$	–3.703	–4.263	–2.163	–2.784	–3.359
$t_{\mu_u=1}$	0.011	2.055	0.833	–1.923	0.409
Log-likelihood	781.536	770.749	793.822	835.985	775.212

Notes. The estimation results of the endogenous regime switching model are reported for each currency. Standard errors are reported in parentheses. $t_{\mu_\ell=1}$ ($t_{\mu_u=1}$) denotes the t-statistic for testing the null hypothesis of $\mu_\ell = 1$ ($\mu_u = 1$).

TABLE 3. REGIME-SPECIFIC CARRY TRADE RETURN (%) WITH TRANSACTION COSTS

Currency	Low volatility regime	High volatility regime
AUD	0.251	–0.100
CHF	–0.019	0.076
EUR	–0.048	0.109
GBP	0.139	–0.017
JPY	–0.153	0.084

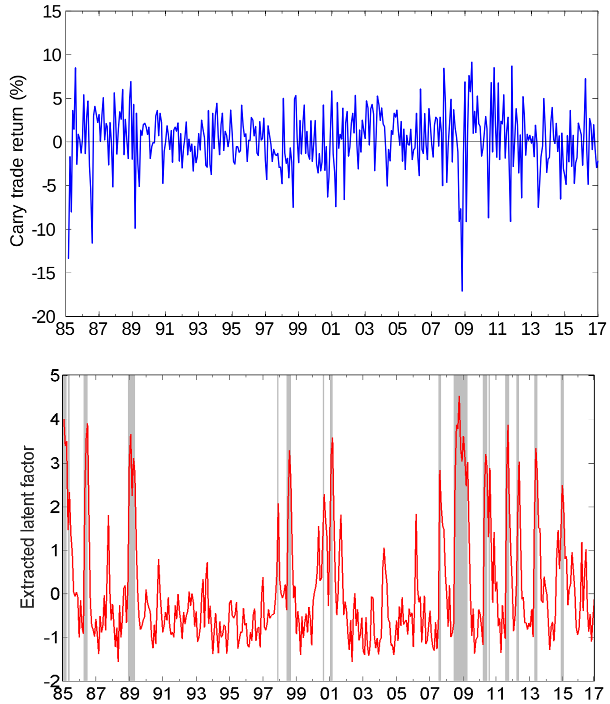
Note. The average excess return (%) to the carry trade with transaction costs is reported for low and high volatility regimes, respectively.

TABLE 4. DATA AVAILABILITY FOR MACROECONOMIC UNCERTAINTY AND EPU

Country	Macroeconomic uncertainty	EPU
Australia	1990.12–2014.07	1998.01–2016.12
Switzerland	1998.07–2014.07	.
Euro area	2003.01–2014.07	1997.01–2014.03
UK	1989.11–2014.07	1997.01–2014.03
Japan	1989.11–2014.07	1987.01–2016.12

Notes. The data availability for the country-specific macroeconomic uncertainty index of Ozturk and Sheng (2017) and the index of economic policy uncertainty (EPU) of Baker et al. (2016) is reported for each country. For Switzerland, no EPU index is available.

(A) AUD



(B) CHF

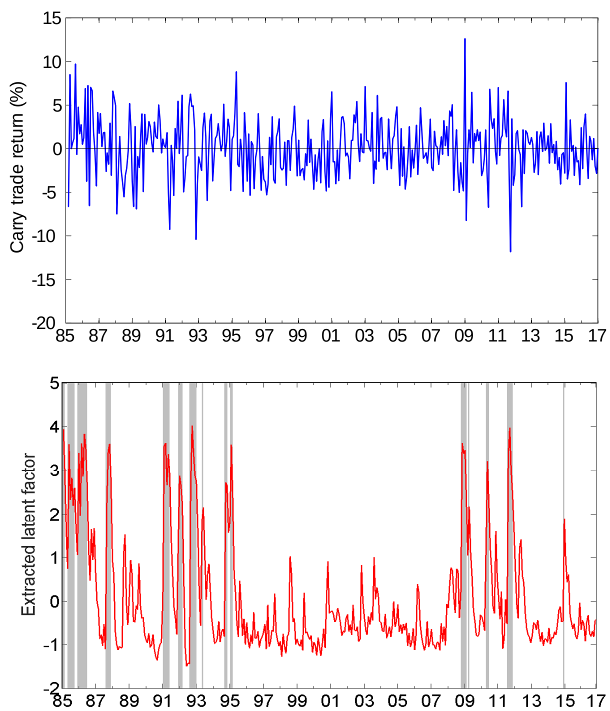
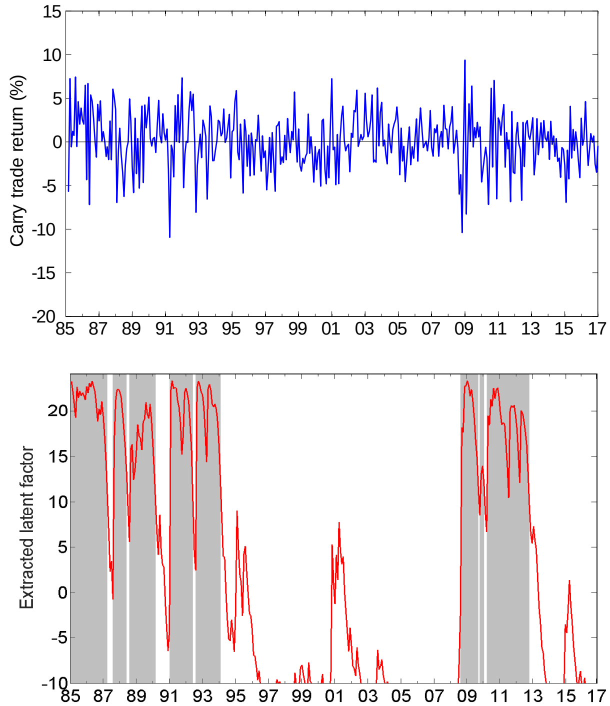


FIGURE 1. CARRY TRADE RETURN (%, TOP) AND EXTRACTED LATENT FACTOR (BOTTOM). SHADED AREAS INDICATE PERIODS THAT BELONG TO A HIGH VOLATILITY REGIME.

(C) EUR



(D) GBP

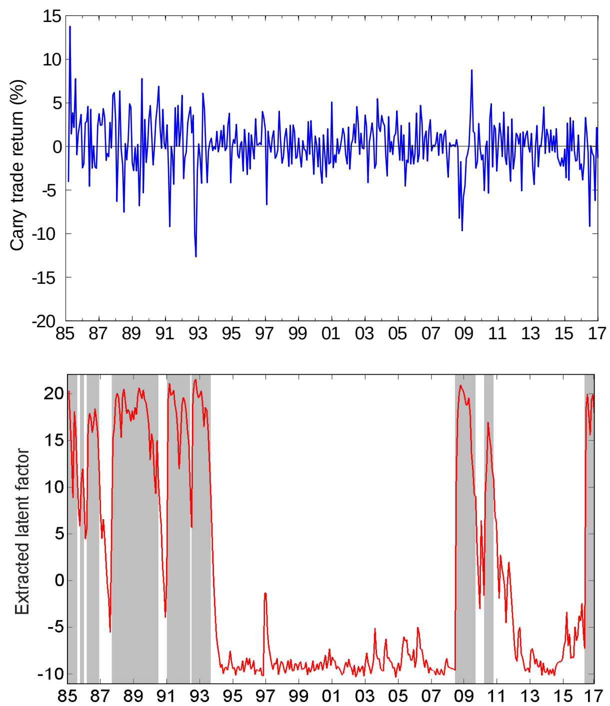


FIGURE 1. CARRY TRADE RETURN (%, TOP) AND EXTRACTED LATENT FACTOR (BOTTOM). SHADED AREAS INDICATE PERIODS THAT BELONG TO A HIGH VOLATILITY REGIME. (CONT'D)

(E) JPY

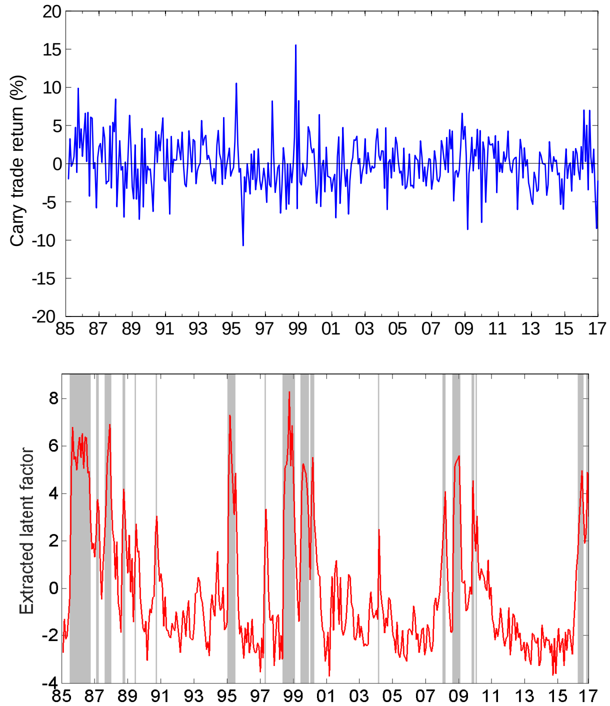
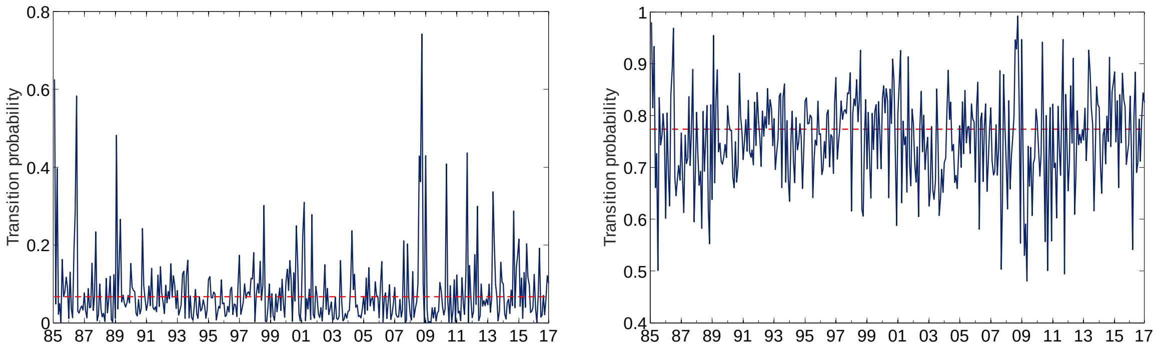
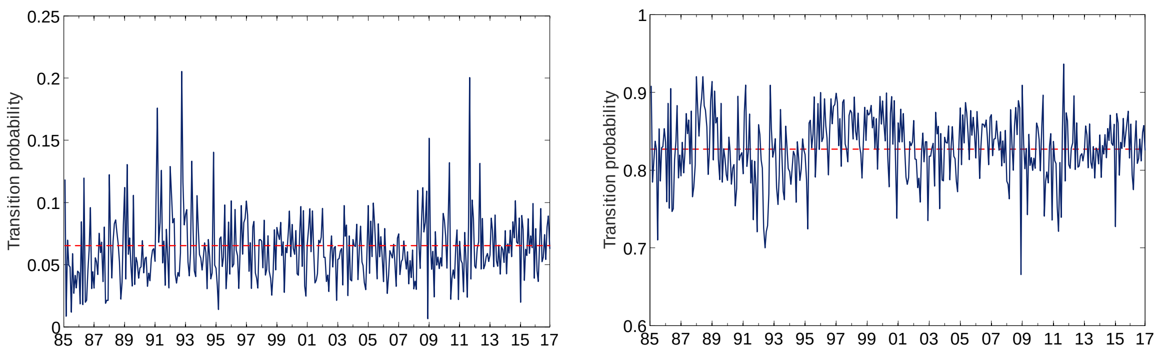


FIGURE 1. CARRY TRADE RETURN (%, TOP) AND EXTRACTED LATENT FACTOR (BOTTOM). SHADED AREAS INDICATE PERIODS THAT BELONG TO A HIGH VOLATILITY REGIME. (CONT'D)

(A) AUD



(B) CHF



(C) EUR

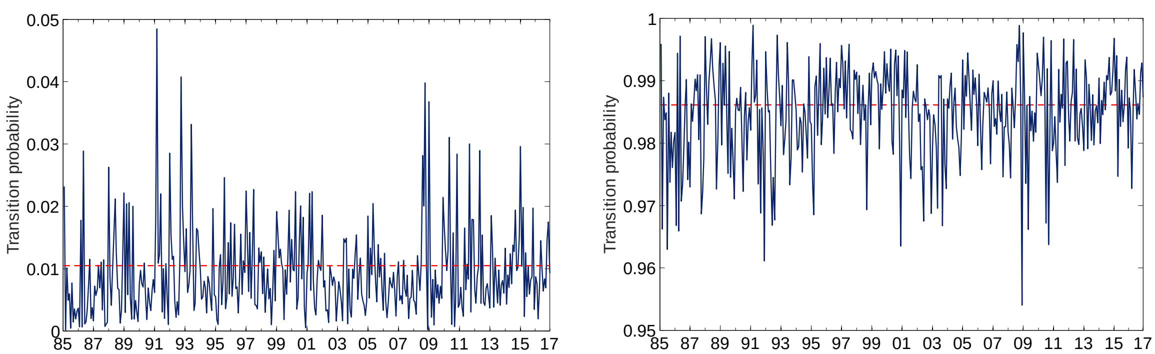
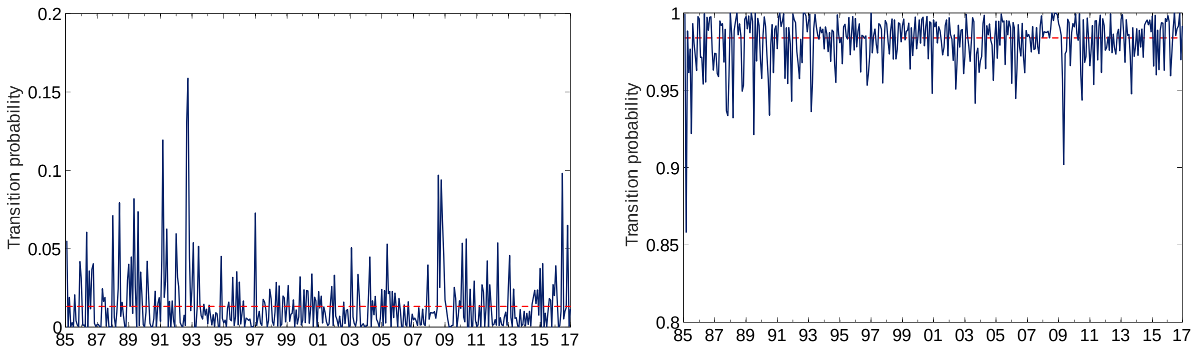


FIGURE 2. ESTIMATED TRANSITION PROBABILITY FROM THE MODEL. THE LEFT GRAPH SHOWS THE TRANSITION PROBABILITY FROM LOW TO HIGH VOLATILITY STATE: THE SOLID BLUE LINE IS FROM THE ENDOGENOUS REGIME SWITCHING MODEL, WHILE THE DASHED RED LINE IS FROM THE CONVENTIONAL MARKOV SWITCHING MODEL. SIMILARLY, THE RIGHT GRAPH SHOWS THE TRANSITION PROBABILITIES OF STAYING AT HIGH VOLATILITY STATE.

(D) GBP



(E) JPY

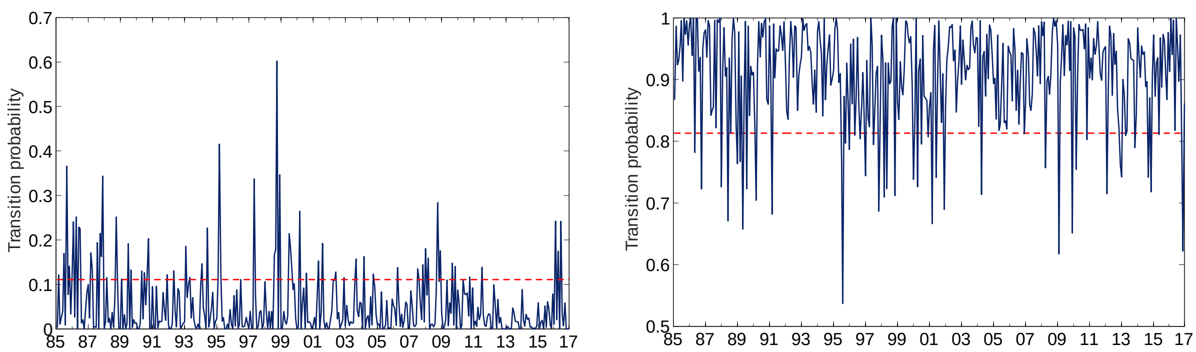


FIGURE 2. ESTIMATED TRANSITION PROBABILITY FROM THE MODEL (CONT'D).

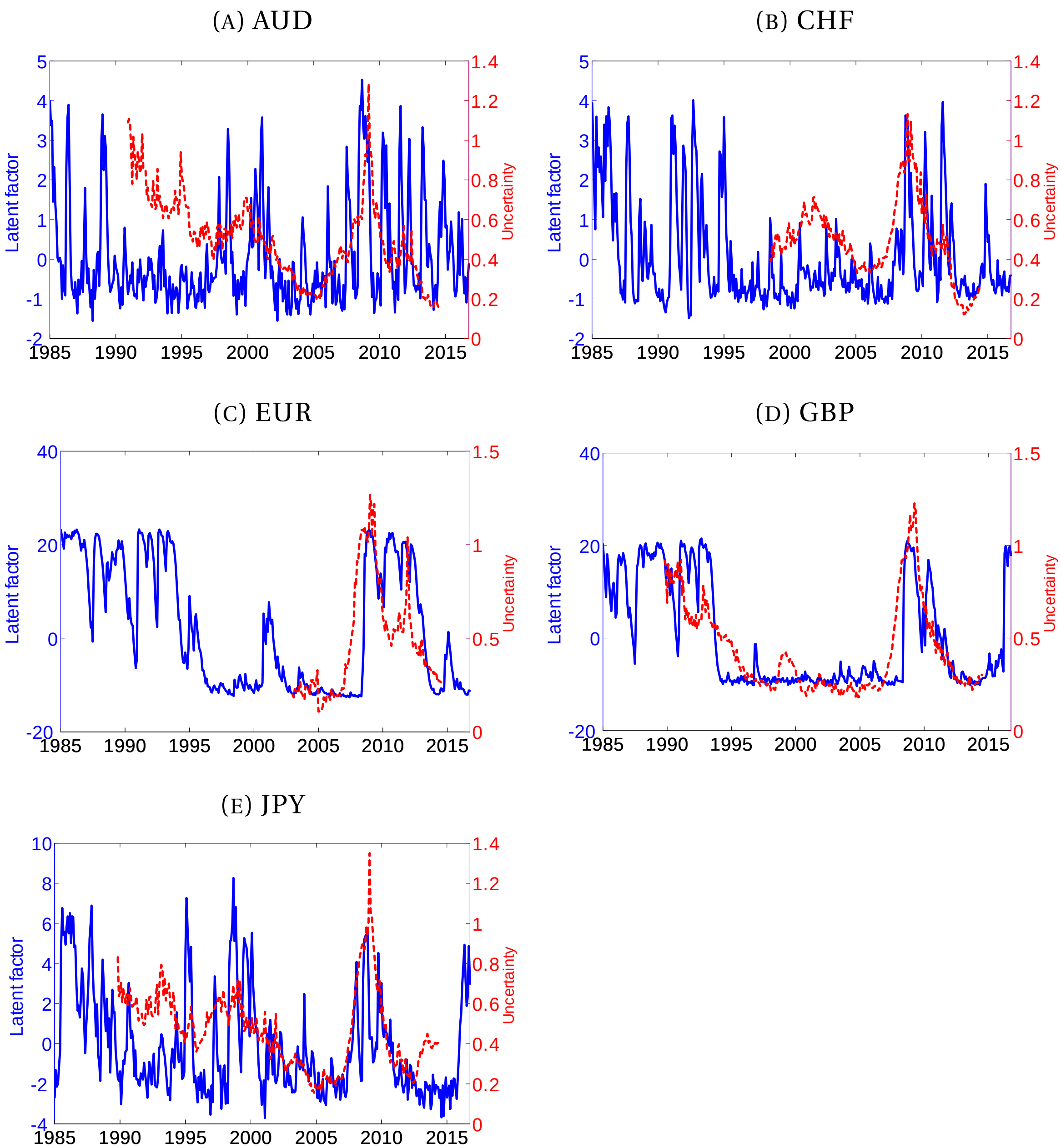
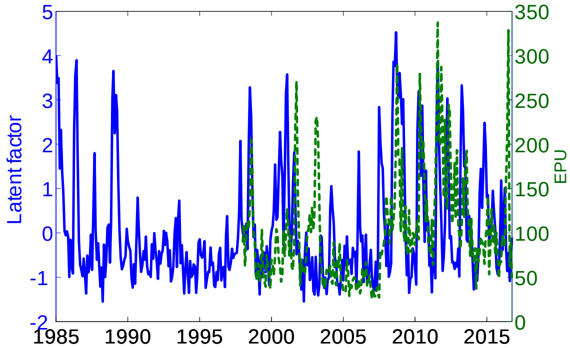
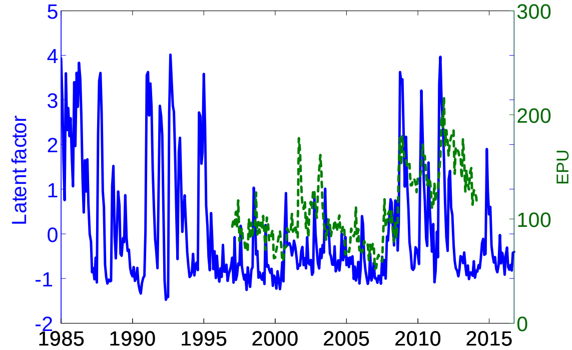


FIGURE 3. EXTRACTED LATENT FACTOR AND COUNTRY-SPECIFIC MACROECONOMIC UNCERTAINTY OF OZTURK AND SHENG (2017). THE SOLID BLUE LINE SIGNIFIES THE EXTRACTED LATENT FACTOR FROM THE ENDOGENOUS REGIME SWITCHING MODEL AND THE DASHED RED LINE DENOTES COUNTRY-SPECIFIC MACROECONOMIC UNCERTAINTY ON THE LEFT AND RIGHT VERTICAL AXIS, RESPECTIVELY.

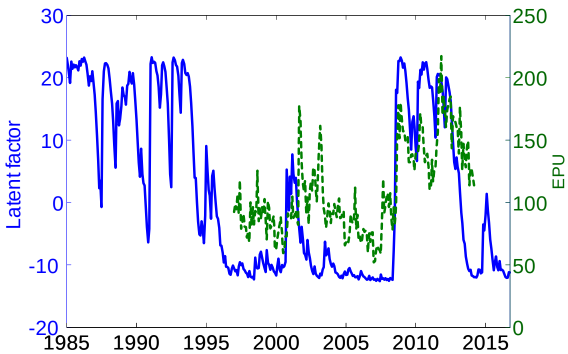
(A) AUD



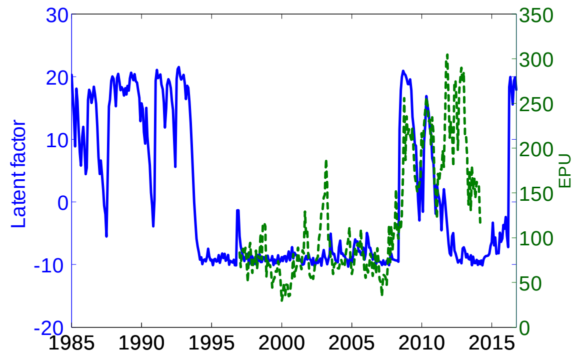
(B) CHF



(C) EUR



(D) GBP



(E) JPY

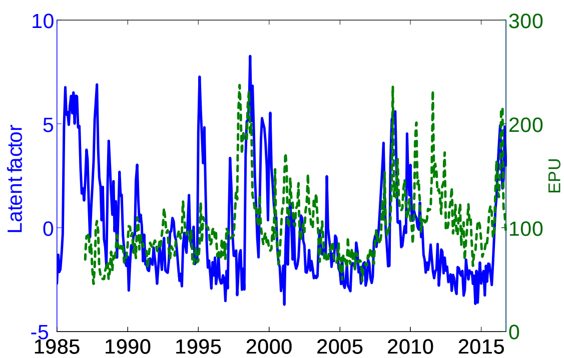


FIGURE 4. EXTRACTED LATENT FACTOR AND COUNTRY-SPECIFIC ECONOMIC POLICY UNCERTAINTY (EPU) INDEX OF BAKER ET AL. (2016). THE SOLID BLUE LINE SIGNIFIES THE EXTRACTED LATENT FACTOR FROM THE ENDOGENOUS REGIME SWITCHING MODEL AND THE DASHED GREEN LINE DENOTES AN INDEX OF COUNTRY-SPECIFIC EPU ON THE LEFT AND RIGHT VERTICAL AXIS, RESPECTIVELY. FOR THE CHF, SINCE THERE IS NO EPU INDEX AVAILABLE FOR SWITZERLAND, THE INDEX OF EPU FOR THE EURO AREA IS DEPICTED INSTEAD.